Impacts of Local COVID-19 on US Air Travel in the Omicron Period

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Introduction

Air travel is an essential component of tourism, commerce, and trade. It serves an intermediary role in business endeavors and connects people globally. The onset of the COVID-19 pandemic in March 2020 severely disrupted the intricate web of the air travel industry. Travel from and within the United States was impacted at a rate only before seen following the September 11 attacks; the Bureau of Transportation Statistics (2020) reported that 17% of US flights were canceled in March 2020, compared to 20% in September 2001. Many countries limited entry to international arrivals from 2020 onward, with Connor (2020) finding that 91% of the world's population resided in countries with limited entry in 2020. Meanwhile, domestic movement in the US was also stifled. Between March and May 2020, 42 states issued stay-at-home orders, and while essential business travel remained, domestic traveler spending decreased by 37.1% relative to pre-pandemic levels. Additionally, according to the World Travel and Tourism Organization (2021) travel and tourism contribution to US GDP dropped by roughly $766 billion in 2020.

This paper aims to bring an empirical understanding, three years into the pandemic, of the extent of COVID-19's continued impact on domestic air travel in the United States. Although the COVID-19 pandemic affected global air travel, this paper focuses solely on domestic air travel, specifically on a 10-month period starting with the beginning of the Omicron period of the pandemic (November 2021). This paper incorporates runway capacity, the traditional estimator of flight capacity, at the 30 major US hub airports (deemed so by the Bureau of Transportation Statistics) alongside COVID-19 related data.

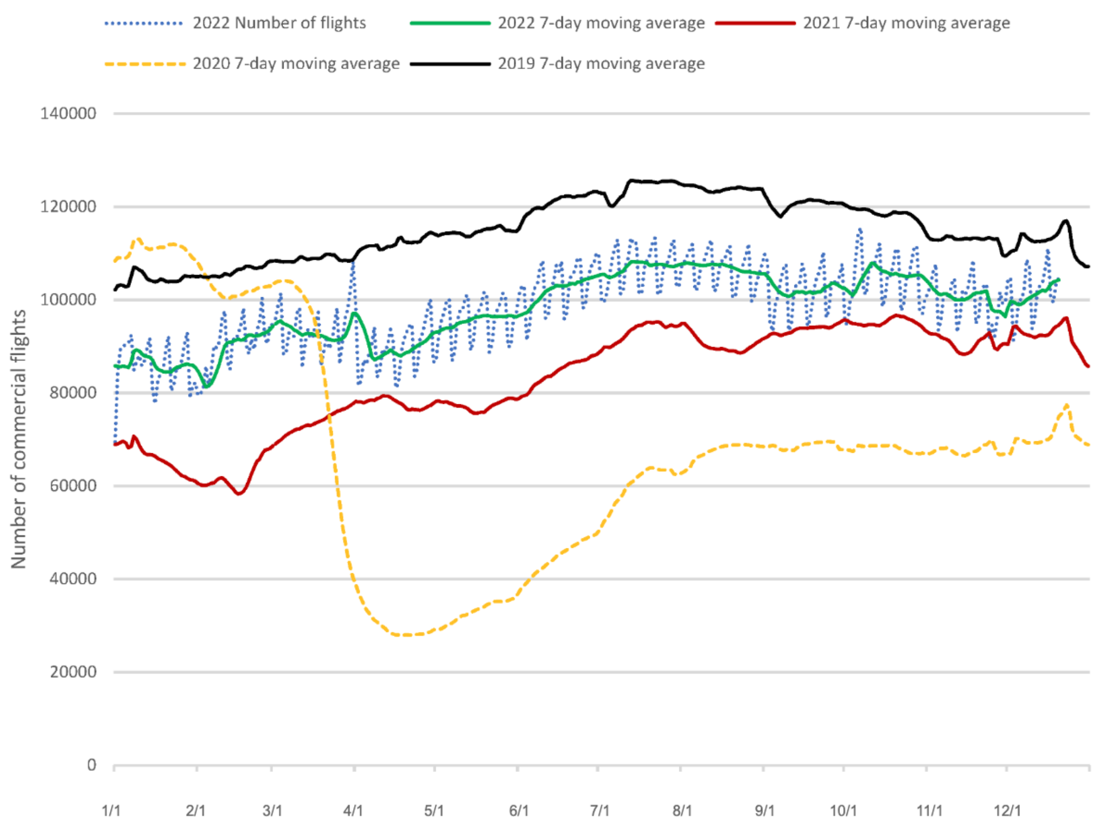
Literature Review

The emerging literature surrounding COVID-19 and air travel centers around several categories–international travel demand, the disease spread on airplanes and in airports, the effectiveness of government subsidies on the air travel industry, and recovery of the industry since March 2020. Literature relevant to this paper focuses on recovery of the air travel industry since March 2020, as well as traditional airport capacity predictors. Previous literature addresses such traditional airport capacity predictors, and several qualitative characteristics of the pandemic and travel demand, but lacks empirical analysis of COVID-related predictors on US flights. This paper aims to fill the gap between traditional empirical studies and preliminary COVID-related studies.

COVID-19 and Air Travel

The initial shock of COVID-19 triggered lockdowns, phobias among travelers, and a shift from the necessity of in-person business communication to remote means. Largely due to this shift, Hall et al. (2020) predicted that the post-pandemic aviation industry was likely to transform drastically from the traditional model. Hall et al. also predicted an increased focus on leisure travel and tourism for airline marketing efforts, as well as space inside aircrafts for comfort and physical distancing. Dube (2023) found that impacts on the value chain of airlines were felt most severely in 2020, with recovery in 2022 (as measured by number of commercial flights) approaching baseline 2019 levels. Dube also found that globally, despite initial recovery beginning in June/July 2020, the Delta variant soon caused a slump in the first months of 2021 (depicted in Figure 1: 2021 7-day moving average). The Omicron variant similarly caused a slump in recovery in the final months of 2021 and first months of 2022 (depicted in Figure 1: 2021 and 2022 7-day moving averages). Overall, Dube points to the initial onset of the pandemic as the largest inhibitor of air travel, while also recognizing the impacts of subsequent variants and the risks associated with further viral evolution. My paper focuses specifically on the period of time in which the Omicron variant accounts for the majority of COVID-19 cases in the United States, rather than globally.

Figure 1: Global Traffic evolution impact and recovery from COVID-19 (Dube 2023)



DeLaura et al. (2021) argued that the traditional drivers of air travel demand surrounding price and service quality are beginning to be overtaken by other considerations, including the current COVID-19 infection rate, vaccine status, government guidelines regarding travel, and use of personal protective equipment. The model I estimate includes these COVID-related variables.

A common method of disease spread mitigation–social distancing–was implemented on aircrafts in 2020 by omitting middle seats. Pearce (2020) found that passenger load factor, a ratio of filled passenger seats relative to total available seats, falls to a maximum of 62% with the omission of the middle seat. Average break-even load factors differ slightly by region, ranging from 75% in North America, Africa, and the Middle East, to 81% in the Asia Pacific region. In the 2019 sample, 97% of airlines that would not break even with 62% load factors would become loss-making. Thus, a mere 3% of sampled airlines (all budget airlines) functioned at break even revenue with passenger load factors below 62%. Airlines set specific benchmarks for load factor according to revenue goals, with most airlines aiming for load factors above 70% to break even. The implementation of social distancing thus marked a significant threat to airline revenue. As of April 2021, passenger airlines abandoned the policy of middle seat vacancy. However, phobias surrounding disease spread continued beyond the removal of travel restrictions or loosening of policies. A study by Zheng et al. (2021) found that 45.1% of respondents chose to resume travel four to six months after the removal of national travel restrictions following the pandemic outbreak.

The lag of policy change to societal behavior change is of particular interest in the period of study in my paper–beginning with November 2021–as at that point, all but 10 US states had removed mask mandates at the state level. The 10 states that remained include several places of study in my paper: California, the District of Columbia, Illinois, and Washington. Between November 2021 and August 2022, the remaining 10 states ultimately eased their mask mandates, though certain requirements remain now in 2023 (such as in healthcare facilities). Not only did mask requirements differ from state-to-state, but they also varied by county. For example, in the state of California, the indoor mask mandate was lifted on March 1, 2022. Los Angeles County maintained its mask mandate for public transport and transportation hubs (including airports) until September 23, 2022. Meanwhile, the mask mandate for patrons of the San Francisco Bay Area's BART rail line ended on October 1, 2022.

In April 2022 the Biden administration extended its nationwide mask mandate on public transportation and in transportation hubs to May 3, to allow for more time to study an emerging Omicron subvariant. However, Shepardson et al. (2022) reported that on April 18, a federal court ruling in Florida deemed the then 14-month long national mask mandate an unlawful overstep of the federal government. Judge Kathryn Kimball Mizelle's ruling stated that "the US CDC had exceeded its authority with the mandate, had not sought public comment and did not adequately explain its decisions". At that point, TSA stopped enforcing mask-wearing in airports and aboard planes.

The efficacy of face masks in mitigating disease spread is widely accepted as strong. Hansen and Mano (2023) find that state mask mandates reduced weekly new COVID-19 cases by 55, hospital admissions by 11, and deaths by 0.7 per 100,000 people on average. However, human behavior under a mask mandate lends itself to risk compensation. Yan et al. (2021) find that Americans subject to local mask orders spend 11-24 fewer minutes at home per day on average and increase their attendance at commercial locations, including hotels and restaurants. They conclude that the net change in COVID-19 transmission with the imposition of a mask mandate is ambiguous due to this risk compensation. Trogen and Caplan (2021) find additional evidence of risk compensation relating to vaccination against COVID-19. Due to the view of the COVID-19 vaccine rollout as the panacea of the pandemic, individuals were less likely to adhere to other mitigation techniques like masking and social distancing. This is an example of the Peltzman effect–when safety measures are implemented, people's risk perception decreases, and thus they make riskier decisions. The Peltzman effect is seen anywhere from contagious disease spread mitigation to automobile safety regulation. My paper explores the role of mask mandates and vaccine distribution in air travel with increases in air travel frequency representing a departure from strict adherence to COVID-19 mitigation.

Traditional Airport Capacity Predictors

DeLaura et al. (2021) indicate that air travel demand is based heavily on the current COVID-19 infection rate, vaccine status, government guidelines regarding travel, and use of personal protective equipment. Traditional airport capacity predictors, rather, base estimates off the number of flights facilitated at an airport on runway capacity, meteorological conditions, runway configurations, and the ratio of arrivals to departures.

Hockaday and Kanafani (1974) were the pioneers of total airport capacity research, focusing on New York's LaGuardia Airport. They define capacity of a runway system as "the maximum flow rate of operations that can be accommodated under specified [meteorological] conditions". They also argue that physical airport capacity, defined as the number of flights an airport can support via landing strips, is the most accurate determinant of the true ability of an airport system to handle air traffic. This statistic is more accurate than other measures such as average delay, average fare, or revenue. The Federal Aviation Administration's Airport Capacity Profiles report (2014) measures the runway capacity of 30 core US hub airports under three different meteorological conditions–visual, marginal, and instrument. Visual conditions exist in the clearest weather, allowing pilots high visibility and ceiling, which is a measure of each aircraft's specific performance capability. Marginal conditions have slightly lower ceiling and visibility, but higher than instrument conditions, which require radar separation between each aircraft due to low visibility. Each of these conditions produce a unique capacity range at each airport, measured in arrivals and departures per hour. These measurements serve as controls in my study.

Data and Methods

In accordance with existing literature, this paper aims to assess the correlation between COVID-related factors at the local level and air travel demand. The chosen period of study is November 2021, marking the onset of the Omicron variant, to August 2022, through which the Bureau of Transportation Statistics database is most recently updated. The dependent variable in the regressions is number of flights, measured in total number of originating flights that depart per month and labeled *totalflights*. The below variables are part of a panel regression of the 30 core US hub airports (as designated by the Bureau of Transportation Statistics) over the 10-month period.

Data in this study come from several sources, including Covid Act Now: US COVID Tracker, the Federal Aviation Administration, the US Census Bureau, the Bureau of Transportation Statistics, and individual airports' audited financial statements. From these data sources and in line with previous literature regarding traditional estimators of air traffic capacity (Hockaday and Kanafani 1974), I identify visual capacity as a control variable. Visual capacity data come from the Federal Aviation Administration's Airport Capacity Profiles. Visual capacity is measured in arrivals and departures per hour and is labeled *visualcap*.

I use Covid Act Now: US COVID Tracker data at the county level to identify the following COVID-related independent variables: the average daily number of new COVID cases per month labeled *cases*, the average daily COVID infection rate per month as a percentage of the US Census Bureau's measurement of county population labeled *caserate*, the percentage of

COVID cases resulting in death per month (labeled *deathrate*), as well as the absolute number of new COVID-related deaths each month (labeled *deaths*), the ratio of the number of those eligible who have received at least one dose of the COVID-19 vaccine (marking the decision to be vaccinated, and labeled *vax*) to population, labeled *vaxratio*, and a dummy variable representing the presence (denoted by 1) or lack of (denoted by 0) a mask mandate at several different levels–the county level, the state level, and the FAA (national) level. County mask mandate data are labeled *countymask*, state mask mandate data are labeled *statemask*, and FAA mask mandate data are labeled *faamask*. I also control for the CDC Transmission Level in each county on the majority of days out of the month, labeled *cdctransmit*. The CDC Transmission Level is reported on an integer scale from 1-3 by the CDC and describes the amount of COVID-19 spread within each county. It informs healthcare facilities on which infection control interventions are most appropriate. I use county-level data for the COVID statistics in accordance with the CDC's "Community Level" information. It allows for greater specificity of COVID landscapes than would state-level data, as different regions within states have varying rates of disease spread, risk level, and vaccination. See Table 1 for variable descriptions and Tables 2 and 3 for summary statistics.

Regression Results

Model 1: $totalflights_i = \beta_0 + \beta_1(visualcap_i) + \varepsilon_i$

Model 1 defines the relationship between total monthly flights and the visual landing capacity at each airport. The regression coefficient for visual capacity is 84.86525, meaning that a unit increase in visual capacity corresponds with approximately 85 additional monthly flights, and is statistically significant at the 5% level ($p<0.05$). The regression yields an R-squared value of 0.5818, meaning that 58.18% of the variation in total monthly flights can be explained by visual capacity.

Model 2: $totalflights_i = \beta_0 + \beta_1(caserate_i) + \beta_2(visualcap_i) + \varepsilon_i$

Model 2 defines the relationship between total monthly flights and the per capita case rate at the county level, while controlling for visual capacity. The addition of the independent variable *caserate* in Model 2 leads to a slight increase in overall R-squared of 0.5882. This implies that the COVID case rate and airport visual capacity explain 58.82% of the variation in total monthly flights at each airport. Additionally, 18.97% of the variation from month-to-month within each airport is explained by the model, while 60.21% of cross-airport total flight variation is explained by the model. Both *caserate* and *visualcap* are statistically significant at the 5% level ($p<0.05$). The coefficient on *caserate* of -43,277.92 implies that a single percentage point increase (0.01) in the COVID case rate is associated with 433 fewer total monthly flights.

Model 3: $totalflights_i = \beta_0 + \beta_1(caserate_i) + \beta_2(deaths_i) + \beta_3(statemask_i) + \beta_4(countymask_i) + \beta_5(faamask_i) + \beta_6(vax_i) + \beta_7(cdctransmit_i) + \beta_8(visualcap_i) + \varepsilon_i$

Model 3 implements the remaining COVID-related independent variables–deaths, various mask mandates, vaccination, and the CDC transmission level by county each month. In this model, several variables emerge as statistically significant at the 5% level ($p<0.05$). These include *caserate*, *statemask*, *countymask*, *faamask*, and *visualcap*. In this model, COVID deaths, vaccinations, and the CDC Transmission Level are not statistically significant. The coefficient on *caserate* implies that a 1% increase (0.01) in COVID cases is associated with approximately 295 fewer total monthly flights. Each mask mandate dummy variable is statistically significant, with the coefficient on *statemask* denoting that the presence of a statewide mask mandate is associated with approximately 573 fewer total monthly flights. The coefficient on *countymask* implies that the presence of a county-level mask mandate is associated with approximately 443 fewer total monthly flights. The coefficient on *faamask*, representing the FAA mask mandate, which presided over all US air travel for six of the ten months studied, is -664.94. This implies that the presence of the Federal Aviation Administration mask mandate is associated with approximately 665 fewer total monthly flights. The coefficient on *visualcap*, similar to Models 1 and 2, implies that a unit increase in visual capacity corresponds with an approximate 85 total flight increase per month.

The model yields an overall R-squared value of 0.6206. This indicates that 62.06% of the variation in total monthly flights can be explained by the regressors in the model. Additionally, 48.82% of the variation in total flights within each airport and 62.15% of the variation between airports can be explained by the model. See Table 4 for a summary of all variable coefficients, significance levels, and robust standard errors.

Conclusion

My study focused on the 10-month time period of November 2021-August 2022, a time in which the Omicron COVID-19 variant emerged and spiked in the United States. I further focused on the 30 airports deemed Core Hub Airports by the Bureau of Transportation Statistics. I ran several panel regressions to determine whether there was a relationship between various COVID-related statistics and the number of passenger flights in the Omicron period. My results demonstrate statistically significant correlations between flights and COVID case rates, state mask mandates, county mask mandates, the Federal Aviation Administration mask mandate, and visual capacity.

I faced several limitations in this study that serve as potential avenues for further analysis. First, I chose to evaluate COVID-19 statistics at the county level due to the CDC's classification of counties as "Community Level". However, large core airports serve a wider customer base than the county they are in. COVID-specific data were accessible at only the county and state levels. The most accurate sample area would be the precise geographic region of residents that patronize each airport. However, that exact area would vary depending on an airport's proximity to other airports.

Ultimately, Model 3 yielded an overall R-squared of 0.6206. The model has substantial explanatory power, but based on the results of Model 1 (R-squared of 0.5818) much of that explanatory power comes from the visual capacity control variable.

This paper adds to a growing group of literature surrounding the COVID-19 pandemic and air travel, with specific focus on the Omicron period. Though COVID-19 vaccinations were readily available worldwide in the period studied, there was still a significant average decline in flights from the 30 US Core airports as Omicron infections spiked, correlated with increases in cases as well as government-imposed mask mandates for disease spread mitigation. For the aviation industry to continue recovering in the coming years, it must anticipate that regardless of vaccination availability and uptake, spikes in COVID-19 cases impact the number of passenger flights that leave the ground.

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Table 1: Variables

Variables	Description	Months	Unit	Source
totalflights	Monthly total number of monthly flights originating at each core airport	11/2021-08/2022	Flights	US Bureau of Transportation Statistics
visualcap	Hourly arrivals and departures per hour under clear weather conditions at each core airport	11/2021-08/2022	Flights	Federal Aviation Administration
cases	Average daily number of new COVID cases each month by county	11/2021-08/2022	COVID Cases	Covid Act Now: US COVID Tracker
caserate	Average daily COVID infection rate by county population each month	11/2021-08/2022	Percentage	Covid Act Now: US COVID Tracker; US Census Bureau
deaths	Number of new COVID-related deaths by county per month	11/2021-08/2022	Deaths	Covid Act Now: US COVID Tracker
deathrate	Percentage of COVID cases resulting in death per month	11/2021-08/2022	Percentage	Covid Act Now: US COVID Tracker
statemask	Presence or lack of state mask mandate for >15 days out of the month	11/2021-08/2022	Dummy	AARP
countymask	Presence or lack of county mask mandate for >15 days out of the month	11/2021-08/2022	Dummy	Covid Act Now: US COVID Tracker
faamask	Presence or lack of FAA mask mandate for >15 days out of the month	11/2021-08/2022	Dummy	Federal Aviation Administration
vax	Number of eligible individuals who have received at least one dose of the COVID-19 vaccine by county	11/2021-08/2022	Individuals	Covid Act Now: US COVID Tracker
vaxratio	Ratio of those who have received at least one COVID-19 vaccine to the total eligible population by county	11/2021-08/2022	Percentage	Covid Act Now: US COVID Tracker
cdctransmit	Amount of COVID-19 spread within each county on an integer scale	11/2021-08/2022	Integer Scale (1-3)	Covid Act Now: US COVID Tracker; CDC

Table 2: Summary Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
totalflights	300	13889.09	6193.06	4471	30042
visualcap	300	134.15	55.66	43.5	264
cases	300	34561.07	73502.9	799	971512
caserate	300	.0081	.0122	.0004	.0968
deaths	300	158.10	242.71	0	1775
deathrate	300	.0118	.0051	.0045	.0332
statemask	300	.16	.3672	0	1
countymask	300	.2533	.4356	0	1
faamask	300	.6	.4907	0	1
vax	243	1767235	1655388	165291	8229922
vaxratio	243	.7732	.1118	.331	.95
cdctransmit	300	2.683	.5810	1	3

Table 3: Panel Summary Statistics

Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
totalflights	N=300 overall n=30 between T=10 within	13889.09	6193.062 6181.385 1137.812	4471 6104.6 8331.793	30042 28449.4 16628.89
visualcap	N=300 overall n=30 between T=10 within	134.15	55.66024 56.51734 0	43.5 43.5 134.15	264 264 134.15
cases	N=300 overall n=30 between T=10 within	34561.07	73502.9 35744.62 64524.86	799 3939.3 -115699.5	971512 184727.6 821345.5
caserate	N=300 overall n=30 between T=10 within	.0080694	.0122503 .0044332 .0114459	.0004003 .0019257 -.0068982	.0967728 .0184008 .0864413
deaths	N=300 overall n=30 between T=10 within	158.0967	242.7129 161.1227 183.6586	0 5.8 -327.7033	1775 662.8 1270.297
deathrate	N=300 overall n=30 between T=10 within	.0117555	.0051072 .0043683 .0027526	.0044569 .0049824 .0052442	.0331998 .0214273 .023528
statemask	N=300 overall n=30 between T=10 within	.16	.3672186	0 0 -.34	1 .5 .96
countymask	N=300 overall n=30 between T=10 within	.2533333	.4356469 .2029665 .3870824	0 0 -.3466667	1 .6 1.05333
faamask	N=300 overall n=30 between T=10 within	.6	.4907165 0 .4907165	0 .6 0	1 .6 1
vax	N=243 overall n=29 between T=8.3798 within	1767235	1655388 1599055 125636.1	165291 216190.4 1008237	8229922 7913906 2083251
vaxratio	N=243 overall n=29 between T=8.3798 within	.7731728	.1118221 .1036734 .0488616	.331 .5335 .5678729	.95 .942375 .8896728
cdctransmit	N=300 overall n=30 between T=10 within	2.683333	.5809595 .1821014 .5525859	1 2.2 .8833333	3 3 3.483333

Table 4: Regression Results

Independent Variables	Model 1	Model 2	Model 3
visualcap	84.86525 (0.000)	84.71937 (0.000)	85.32594 (0.000)
caserate	–	-43277.92 (0.000)	-29511.53 (0.000)
deaths	–	–	-.2629377 (0.420)
statemask	–	–	-572.8928 (0.026)
countymask	–	–	-443.353 (0.035)
faamask	–	–	-664.94 (0.000)
vax	–	–	-.0000893 (0.794)
cdctransmit	–	–	-126.9289 (0.237)
Number of Observations	N=300 n=30 T=10	N=300 n=30 T=10	N=300 n=30 T=10
R-Squared	Within = .0000 Between = .6021 Overall = .5818	Within = .1897 Between = .6021 Overall = .5882	Within = .4882 Between = .6215 Overall = .6206

P-values in parentheses